

Empirical Implications and Economic Model

The theoretical model implies that demand for unhealthy foods at time t will be a function of income, prices, visceral factors, and health at time t . To test whether visceral influences weaken the impact of health information on food choices, we also include the interaction of visceral factors and nutrition information. Empirically, demand for unhealthy food in the current period can be specified as follows:

$$F_{it} = \beta' X_{it} + u_i + e_{it}, \quad (8)$$

where F_{it} is the amount of unhealthy food individual i consumes at each eating occasion t , X_{it} is a vector of the aforementioned parameters—income, prices, current health status, visceral factors—and the interaction of dietary information and visceral influences, u_i is the individual effect, and e_{it} is the individual, time-specific error term. If there is more than one observation for an individual, as there is in this study, ordinary least squares (OLS) estimates will yield inefficient parameter estimates if the error terms are correlated across observations for a given individual.

A random-effects (RE) model will yield efficient and consistent estimates as long as the individual specific disturbance (u_i) is uncorrelated with the other regressors, X_{it} . However, given the interdependence of current health, dietary awareness, and food choices, this condition will likely not be met. For example, an individual recently diagnosed with diabetes may be more aware of diet and nutrition. This same person would also have greater incentives to improve his or her diet quality and manage the timing of his or her meals. Not accounting for this health condition in the RE estimator would then bias estimates on both the impact of dietary awareness and the interval between meals.

As such, a fixed-effects (FE) model, as specified below, will yield consistent estimates as long as the remaining individual-specific, time-specific disturbance (e_{it}) is also uncorrelated with the regressors (Green, 1990):

$$(F_{it} - \bar{F}_i) = \beta' (X_{it} - \bar{X}_i) + (e_{it} - \bar{e}_i), \quad (9)$$

where $\bar{F}_i$, $\bar{X}_i$, and $\bar{e}_i$ represent individual averages. Continuing with the previous example, a fixed-effects estimator allows one to tease out the impact of time-varying variables, such as the interval between meals. In this case, the FE estimates would measure the impact of meal timing on diet quality for a given individual with specific health conditions and dietary awareness. If, however, the time-specific disturbances are also correlated with the regressors, a fixed-effects model with instrumental variables (FE-IV) can be used to obtain unbiased estimates (Evans et al., 1993). Theoretically, there is reason to suspect that the error terms will be correlated with the explanatory variables because some visceral factors, such as how long one goes between meals, are arguably endogenous and/or possibly measured with error. Thus, we attempt to circumvent this issue through the use of instrumental variables.

We use Stata 9.0 for our empirical analysis. Specifically, we use xtset to identify the nature of our panel data. We specify each individual as the panel variable and each meal as the time variable. We then use xtivreg, a fixed-effects instrumental variable (FE-IV) estimator that uses a two-stage, least-squares within estimator. We also employed random-effects (RE) and fixed-effects (FE) estimators, using generalized least squares. However, the Hausman test statistics indicate that these results were biased.⁶ We therefore only describe variables used in the FE-IV estimation and limit our discussion and presentation of these FE-IV results.

⁶We do not reject the null-hypothesis that the difference between the FE and FE-IV coefficients are not systematic for one model. However, even if the null hypothesis is rejected, FE-IV estimates are consistent.